ANL/ESD-22/2

Vehicle Residual Value Analysis by Powertrain Type and Impacts on Total Cost of Ownership

Energy Systems Division

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Vehicle Residual Value Analysis by Powertrain Type and Impacts on Total Cost of Ownership

by
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LIST OF ACRONYMS

AFV	alternative fuel vehicle
ANL	Argonne National Laboratory
ARR	adjusted retention rate
BEV	battery electric vehicle
DOE	U.S. Department of Energy
EPA	U.S. Environmental Protection Agency
HEV	hybrid electric vehicle
ICEV	internal combustion engine vehicle
KBB	Kelley Blue Book
LDV	light-duty vehicle
MSRP	manufacturer’s suggested retail price
MY	model year
OEM	original equipment manufacturer
PEV	plug-in electric vehicle
PHEV	plug-in hybrid electric vehicle
SUV	sport utility vehicle
TCO	total cost of ownership
TMV	True Market Value
VMT	vehicle miles traveled
WLS	weighted least squares

VEHICLE RESIDUAL VALUE ANALYSIS BY POWERTRAIN TYPE AND IMPACTS ON TOTAL COST OF OWNERSHIP

ABSTRACT

Vehicle depreciation is a key factor in determining the total cost of vehicle ownership and consumer purchase behavior. This report examines how light-duty-vehicle residual values have evolved over time for conventional and advanced vehicle technologies, accounting for important factors such as market segment, size class, and country of assembly. Advancements in electric vehicle technology have led to plug-in vehicles exhibiting depreciation curves similar to those of conventional vehicles. This report compares two methods for determining depreciation trends (snapshot method and time-series method) in order to identify potential impacts on calculating vehicle total cost of ownership given differing data availability.

1. INTRODUCTION

Since the Chevrolet Volt and Nissan Leaf were first introduced in the United States in 2010, plug-in hybrid electric vehicle (PHEV) and battery electric vehicle (BEV) sales have increased significantly. The market share of plug-in electric vehicles (PEVs), comprising PHEVs and BEVs, is growing. PEVs accounted for over 3% of light-duty-vehicle (LDV) sales in the U.S. in the first ten months of 2021 (ANL 2021). PEVs are available in a wide range of size classes and a growing number of makes and are experiencing rapid advances in technology (DOE and EPA 2021).

However, market penetration of these PEVs is highly dependent on their cost competitiveness; it is unlikely that either consumers or automakers will be incentivized to invest in PEVs if they are not economically comparable to or better than conventional internal combustion engine vehicles (ICEVs). While PEVs tend to be more expensive to purchase than their conventional gasoline-powered counterparts, they also offer lower operational costs. Total cost of ownership (TCO) analyses of LDVs examine relevant vehicle ownership costs, including costs for both purchasing and operating the vehicle. Comprehensive TCO studies examine all potential costs, including depreciation, financing, fuel costs, insurance, maintenance and repairs, and taxes and fees. This approach provides a holistic cost comparison between vehicles with various characteristics, including between those with different powertrains.

Comprehensive TCO analyses typically find that depreciation is the largest cost component, especially in the first few years of the vehicle's life (Hamza et al. 2020; AAA 2019; Burnham et al. 2021). Since most new-car buyers do not own their vehicle for the entirety of its lifetime, depreciation is arguably the most important consideration in a new vehicle's TCO. Depreciation is understood most simply as the difference between the price of a new vehicle and its residual value after a given time. While new vehicle prices are well understood and can be modeled using manufacturer's suggested retail price (MSRP) or dealer listing prices, residual values are more varied and less well understood, especially for newer, advanced-powertrain vehicles. Therefore, examining how vehicles with advanced powertrain technologies, such as

PHEVs and BEVs, retain their value is crucial for identifying when these vehicles become economically comparable to conventional gasoline-powered counterparts.

Understanding the residual value beyond the first owner is important for understanding vehicle sales on the used market, which is a factor in determining how readily new technology reaches economically disadvantaged communities, who disproportionately drive older vehicles. Automakers and financing providers have a stake in accurately estimating residual value as well. Lease contracts typically include a forecast residual value at which a lessee can purchase a vehicle at the end of the lease.

In general, many factors affect the residual value of used vehicles. The National Automobile Dealers Association, Autoblog, Consumer Reports, Kelley Blue Book (KBB), and Edmunds all provide estimations of used-car resale values. The major factors these providers utilize when determining price include vehicle make, model and model year (MY), mileage, location, overall condition, and some other vehicle characteristics such as specific trim lines or additional equipment. Variation is especially evident in the case of PEVs, where battery performance and driving range, as well as accessibility to charging, may have a large effect on residual value. Additional factors such as market fluctuations, economic impacts, and various incentives at the federal, state, and local levels also affect depreciation; many of these exogenous factors are not directly captured in our analysis.

In a recent multi-lab TCO report (Burnham et al. 2021), we used the “snapshot method,” which examines multiple MYs at one point in time, for example, by looking at MYs 13–19 in 2020, to quantify generalized depreciation trends for vehicles with various characteristics. Since then, we have obtained a dataset with historical market value estimates which allows us to examine one MY over time, for example, by looking at MY16 in 2017-2021, henceforth referred to as the “time-series” method. This new dataset allows us to both examine depreciation trends over various MYs, amid recent rapid advancements in PEV technology, and quantify the potential impact on our recent TCO calculations derived from using the “time-series” method rather than the “snapshot” method.

The objective of our study is to examine how different powertrains’ residual values have evolved over time amid rapidly improving PEV technology. We analyze this evolution using historical data, accounting for important factors such as market segment, size class, and country of origin of the automobile original equipment manufacturer (OEM). We also develop a method for estimating the residual value of recent MYs, for which we do not yet have many months of data, which allows us to investigate depreciation of even the most recent MYs. Our second objective is to compare depreciation rates between the “snapshot” and “time-series” methods/data in order to identify the potential impact on recent TCO calculations.

1.1. LITERATURE REVIEW

While several studies have explored the resale value of PEVs, few, if any, comprehensive analyses of depreciation trends over time have been completed, owing to the scarcity of data. Furthermore, because of rapidly changing and improving advanced powertrain technology, it is imperative to continue to reassess residual value differences across powertrains to keep up with developments in technology. In 2012, Propfe et al. compared the residual value of vehicles with conventional and advanced powertrains using data from the German market; however, PEV data were extremely limited at that time, so they used assumptions from other sources to estimate the residual value of these vehicles. Later, in 2016, Zhou et al. analyzed residual value across different powertrains using adjusted retention rate (ARR). Retention rate is proportional to residual value for any single vehicle; it provides the percentage of initial value retained, while residual value is the actual dollar value of the vehicle. In that study, the adjustment accounts for federal PEV incentives that reduce the cost to the consumer below the MSRP. They found that PEV retention rates are comparable to those of hybrid electric vehicles (HEVs) and conventional models in the early years but somewhat lower at three years and beyond. However, 3-year-old PEV data were still limited in 2016. A 2017 report by Moody's Analytics likewise found that PEVs depreciate similarly to conventional counterparts in years one and two but depreciate more in years three and four (Vogan 2017).

In 2019, Guo and Zhou used True Market Value (TMV) data from Edmunds to examine residual value in a follow-up study to the 2016 Zhou et al. publication. They found that the long-range, high-performance Tesla Model S holds value better than any other vehicle type evaluated. HEVs and PHEVs are comparable to each other and hold slightly less value than conventional models, but significantly more than short-range BEVs. However, short-range BEVs were shown to have a faster improvement in 3-year ARR than any other powertrain from MY13 to MY14. Schoettle and Sivak (2018) explored the resale value in 2018 of different powertrains using MSRPs from the U.S. Environmental Protection Agency (EPA) and private-party values from KBB. Their analysis of MYs 2011–2015 similarly indicated that, when accounting for federal incentives, PHEVs retained their resale value as well as conventional counterparts while BEVs lost resale value most quickly. A report by ING Economics in 2019 focused on BEVs in the European market, but similarly found that the Tesla Model S held value better than all other powertrain types and that newer BEV models showed improvement in residual value (Erich, 2019). Interestingly, they also found that five-year residual value increased with electric range.

iSeeCars.com, an automotive research firm and car search engine, has analyzed new- and used-car sales data to obtain 3- and 5-year depreciation percentages for specific vehicle models as well as averages within each powertrain technology. In both a 2019 and a 2020 report, they found that PHEVs and HEVs depreciate less than BEVs (Blackley 2019, 2020). In their 2020 and 2021 reports (Blackley 2020, 2021), they found that the Tesla Model 3 held its value better than any other vehicle on the market (regardless of powertrain), consistent with other studies that find that Tesla models hold their value extremely well. A recent study by Fleet Forward and Vincentric analyzing MY20 and MY21 alternative fuel vehicles (AFV) in the U.S. market (Brown 2021) found that HEVs held value the best, followed by PHEVs and then BEVs. It also found that Teslas held value well, though they were negatively impacted by the absence of the federal incentive. However, these estimations were based on future projections rather than historical data. A recent study by Li and Chen (2020) evaluated the residual value of BEVs in China, separating the power battery from the vehicle itself. Although they used a very limited set of vehicle models, they found that BEVs lost value significantly faster than their ICEV counterparts, indicating that BEVs cannot develop independently in China without federal incentives. Hamza et al. (2020) collected real-world price data from KBB to model resale value in their TCO calculation. Similarly to the studies by Guo and Zhou (2019) and Schoettle and Sivak (2018), they found that PHEVs and ICEVs held value at relatively the same level, while BEVs experienced 11% lower 5-year retention.

An increasing number of TCO studies include depreciation as a factor in their analysis. However, this approach raises a new challenge: estimating depreciation rates for new vehicle types. Many researchers have simply avoided directly addressing this emerging complexity, instead using the assumption of equal depreciation across powertrains (Hagman et al. 2016; Kampker et al. 2018; Morrison et al. 2018). Some studies have modeled depreciation as a function of vehicle miles traveled (VMT) (Wu et al. 2015) or included battery salvage (Letmathe and Suares 2017). Other studies have, on the other hand, attempted to differentiate between powertrains more broadly: Hamza et al. (2020), Lévay et al. (2017), and Breetz & Salon (2018) generalized powertrain depreciation trends from a small sample of vehicle models, and Gilmore and Lave (2013) used auction price data to model depreciation rates.

However, most of the residual value studies analyze a limited number of vehicle models and trim lines. Some do not account for federal incentives, which is a limitation given that considering federal incentives more accurately represents the true price for a buyer. Moreover, none of these studies explore depreciation trends over different MYs, instead simply examining depreciation across powertrains at one point in time. Using the former approach, however, is especially insightful in that it allows us to compare current depreciation rates in the context of past trends, rather than isolated within a single year.

2. DATA AND METHODOLOGY

2.1. DATA SOURCES

To assess the residual value of various vehicles, we used data provided by Edmunds.com on the value of used LDVs (Edmunds 2020). Edmunds provides TMV of used vehicles based on real transactions. These estimates are updated monthly and reflect market conditions. We selected Edmunds over other data sources because many of the other third-party sources such as KBB, Autoblog, and Consumer Reports only provide TCO-formulated depreciation costs, which are based on projected costs rather than actual transaction prices. Furthermore, while we are aware of other sources that provide self-reported transaction data, such as truecar.com, it is challenging to validate the self-reported values with the true transaction prices. Finally, while there are sources such as KBB, Cars.com, Craigslist, and Facebook Marketplace that provide vehicle listing prices, it is difficult to ascertain the relationship between listing price and transaction price. Our research purpose is to quantify the general vehicle depreciation trends by vehicle size class, market segment, and powertrain type, not by make and model. As such, we selected one data source, Edmunds, for consistency and because its TMV data are based on real transactions. Future research is needed to compare the market value estimates from different resources. All TMV values are for private-party transactions involving used vehicles in clean condition. Typically, private-party purchase costs are lower than would be expected at a dealership, as dealerships need to cover costs related to salaries, overhead, and profit (Choksey 2020).

Results presented in this report come from two TMV datasets from Edmunds. The first, used in TCO calculations and referred to as the “snapshot data,” contains TMV from July 2020 for MYs 2013–2019. This method provides a snapshot of TMV estimates at the time of collection: for example, TMVs at year one are estimates of MY2019 in July 2020 and TMVs at year three are estimates of MY2017 in July 2020. The second dataset, referred to as the “time-series data,” contains historical monthly TMV estimates from January 2013 through April 2021 for all trim lines over MYs 2010–2021 for the selected vehicle models. This second dataset allows us to track the residual value of a single MY and vehicle model over time rather than just obtaining a snapshot of the residual value of different MYs, as provided by the first dataset.

For the snapshot data, TMV values assumed 12,000 annual VMT, which lies between the average annual VMT for cars and for light trucks reported by the Transportation Energy Data Book (Davis and Boundy 2020). To obtain a national average while accounting for geographical variation, TMV values were averaged across 51 zip codes (one in each of the 50 U.S. states and Washington, D.C.). When including all MYs and models, the standard deviation of mean TMV by zip code is about $300 for ICEVs and less than $200 for all other powertrains. We performed a sensitivity analysis of annual VMT and observed little effect on TMV for adjustments under approximately 3,000 miles per year. Note that depreciation is a function of both vehicle age and VMT (Propfe et al. 2012, Kleiner and Friedrich 2017). However, the TMV data we have do not support analysis identifying their correlation with VMT (see Section 2.3.2 for details).

For the time-series data, all TMV estimates provided by Edmunds are national average values. Rather than a constant annual VMT for all vehicles (as in the case of the snapshot data), Edmunds provides a median mileage estimate for all TMV values which allows us to calculate the average annual VMT (mean 9,071; standard deviation 2,345). This average is lower than what is reported in the Transportation Energy Data Book. We use the new vehicle market entry month as the start date for each vehicle and calculate the VMT each year thereafter. This method knowingly underestimates the mean annual VMT, since the new-vehicle market entry is a lower bound for the first time that a vehicle could accumulate mileage; however, it is very difficult to determine the calendar month when each vehicle model was typically sold to the first owner. Table 1 shows the mean annual VMT for all four powertrains considered (ICEV, HEV, BEV, and PHEV), for the mass-market and luxury-market segments, and for the car and sport utility vehicle (SUV) size classes. Note that the values in Table 1 are the average of all MYs; newer vehicles have less annual VMT and less variation, likely as a result of limited data points, shown in Figure 1. The mean annual VMT does not vary greatly between vehicles with different powertrains, market segments, or size classes, as shown in Table 1. While there is some variation between the two datasets and between various vehicle characteristics, it is less than the range within which we observed little effect on TMV in the sensitivity analysis.

Table 1: Mean Annual VMT by Various Vehicle Characteristics

Powertrain	ICEV	HEV	BEV	PHEV	Average
Mean Annual VMT	9,011	9,590	8,838	8,303	9,071

Market Segment	Mass Market	Luxury	Average
Mean Annual VMT	9,560	7,985	9,071

Size Class	Car	SUV	Average
Mean Annual VMT	8,931	9,501	9,071

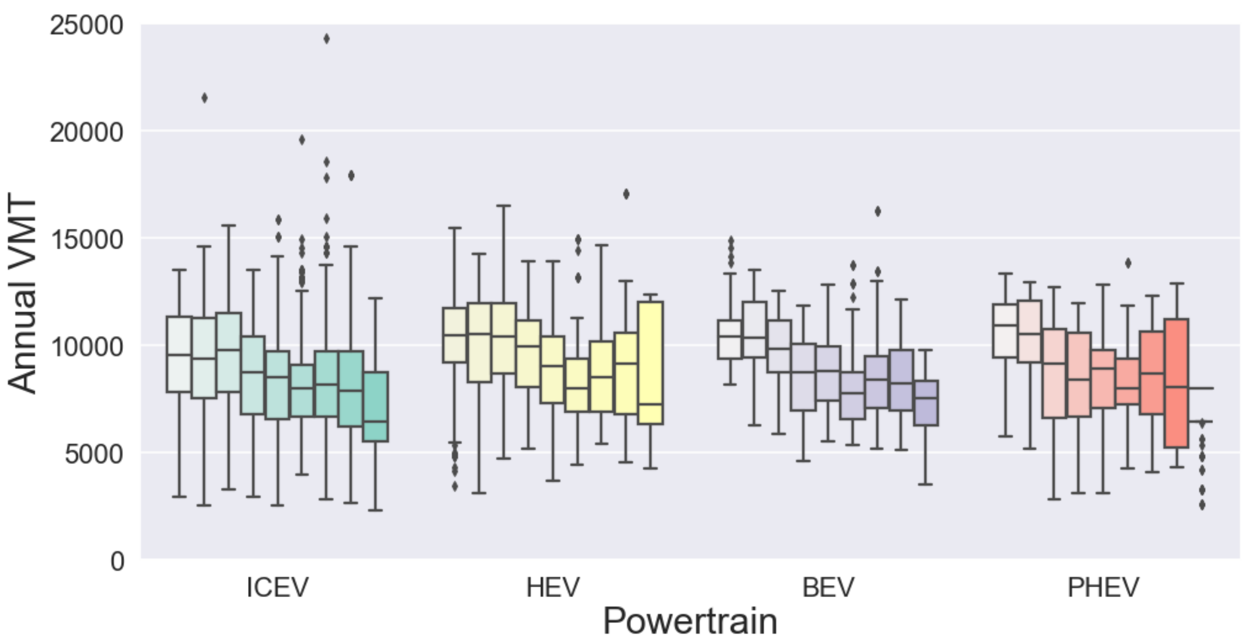

Figure 1: Annual VMT by MY and Powertrain Type. Within each powertrain, each box and whisker represent MYs 2012–2020 in order from left to right.

We selected 23 makes and 106 models (shown in Table 2) to cover different powertrain technologies, size classes, market segments, and various popular manufacturer brands and originating countries. Table 2 shows these specific vehicles; while most vehicles were used for both types of depreciation analysis, some models were only analyzed by the snapshot method (denoted in italics and red text), while others were only analyzed by the time-series method (denoted by an underline and blue text). The selection of vehicles for the snapshot method was described in greater detail in a recent report (Burnham et al. 2021). For the time-series method, we began by selecting the best-selling non-conventional vehicles; our analysis included 38 best-selling PEV models and 25 best-selling HEV models in the U.S., accounting for 94% and 87% of total 2020 PEV and HEV sales (ANL 2021). To compare depreciation rates of AFVs and ICEVs, we picked conventional ICEV versions of the PEV and HEV models (e.g., Kia Soul, Kia Soul EV). When a direct conventional counterpart was unavailable, we picked a comparable model that fell into the same EPA size class and MSRP range (e.g., Nissan Leaf, Nissan Altima). In total, our time-series analysis included 38 ICEV models.

Edmunds provided MSRP data for all vehicles in the time-series dataset. We obtained PEV federal incentive data from the IRS website (IRS 2020). For models for which federal incentives were being phased out during 2019 or 2020 (GM, Tesla), we computed a 2019 or 2020 sales-weighted average incentive, respectively (ANL 2021). We obtained size-class data and new-vehicle market entry dates from the FuelEconomy.gov website (DOE and EPA 2021). For cross-validation, we compared the dates for vehicle release from FuelEconomy.gov with Edmunds, finding general agreement between the two sources. We aggregated depreciation by market segment (luxury/mass-market) as defined by Wards (Wards Intelligence 2021).

Table 2: Makes and Models Selected for Analysis. Vehicles in plain text were considered in both depreciation datasets; italicized vehicles were analyzed only by the snapshot method (red), and underlined vehicles only by the time-series method (blue).

Make	ICEV	BEV	PHEV	HEV
Acura	MDX, ILX, RLX			MDX, RLX Sport Hybrid
Audi	A4, Q7	E-tron	*Q5*	A8
BMW	5 Series, 7 Series, X6	i3	5 Series Plug-in, 7 Series Plug-in, i8, *X3*	
Cadillac	XTS			
Chevrolet	Malibu, Spark, <u>Cruze</u>	Bolt EV	Volt	Malibu Hybrid
Chrysler	Pacifica			Pacifica Hybrid
FIAT	500	500e		
Ford	Fusion, Escape		Fusion Energi	Fusion Hybrid, *Escape Hybrid*, C-Max Hybrid
Honda	Civic, Accord	Clarity	Clarity	Accord Hybrid, CR-V Hybrid, Insight
Hyundai	Sonata, Kona	Ioniq Electric, Kona Electric	Sonata Plug-in, Ioniq Plug-in	Sonata Hybrid, Ioniq Hybrid
Kia	Optima, Soul	Soul EV, Niro EV	Optima Plug-in, <u>Niro Plug-in</u>	Optima Hybrid, Niro
Land Rover	Range Rover, Range Rover Sport		*Range Rover Plug-in, Range Rover Sport Plug-in*	
Lexus	ES350			ES300h, NX300h, <u>RX450h</u>
Lincoln	MKZ		*Aviator Plug-in*	MKZ Hybrid
Mercedes-Benz	GLE-Class	B-Class Electric Drive	GLC-Class	
Mitsubishi	Outlander		Outlander Plug-in	
Nissan	Sentra, Altima	Leaf		
Porsche	Panamera, Cayenne	*Taycan*	Panamera Plug-in, Cayenne Plug-in	
Subaru	Crosstrek		Crosstrek	
Tesla		Model S, Model X, Model 3, Model Y		
Toyota	Camry, RAV4, Highlander, Avalon, *Corolla*	*RAV4 EV*	Prius Prime	Camry Hybrid, RAV4 Hybrid, Highlander Hybrid, Avalon Hybrid, Corolla Hybrid, Prius, Prius c
Volkswagen	Golf GTI	E-golf		
Volvo	<u>XC90</u>		<u>XC90 Plug-in</u>	

2.2. METHODOLOGY

2.2.1. Initial Vehicle Valuation

When calculating depreciation, we used MSRP rather than new-vehicle transaction price as the initial value, because of data limitations; actual new-vehicle transaction prices for all MYs are difficult to ascertain. However, as most vehicles are sold beneath the MSRP, we examined the potential effect of this approach on our results. We gathered Starting Market Average values, an average new-vehicle transaction price based on actual recent transactions, from Truecar, and new-vehicle listing prices from Cars.com for all trim lines of all MY2020 and MY2021 vehicles listed in Table 2, if available (Truecar 2021; Cars.com 2021). For the listing-price data, we used Argonne National Laboratory's zip code, 60439, as the location, but allowed for results within any distance; our results included listings up to 2,000 miles away. Therefore, the listing-price data came from many different parts of the country. Both Truecar and Cars.com provided the MSRP in addition to the Starting Market Average/listing price for each trim line. We used this MSRP value for our comparison to ensure that all trim lines, add-ons, and extra-equipment characteristics were identical between the MSRP and market value/listing price.

Figure 2 shows the spread of new-vehicle listing prices as a percentage of MSRP for four powertrain types. Note that the difference between MSRP and listing price is generally small and that there isn't a large difference between the different powertrains. The most significant difference is that BEVs are sold closer to MSRP than other powertrain types; this observation is consistent with other studies (Tal et al. 2017). This means that using MSRP underestimates the retention rate of the other powertrain types more than it underestimates the retention rate of BEVs. However, in analyzing technology trends over time within a single powertrain, this effect is not as relevant.

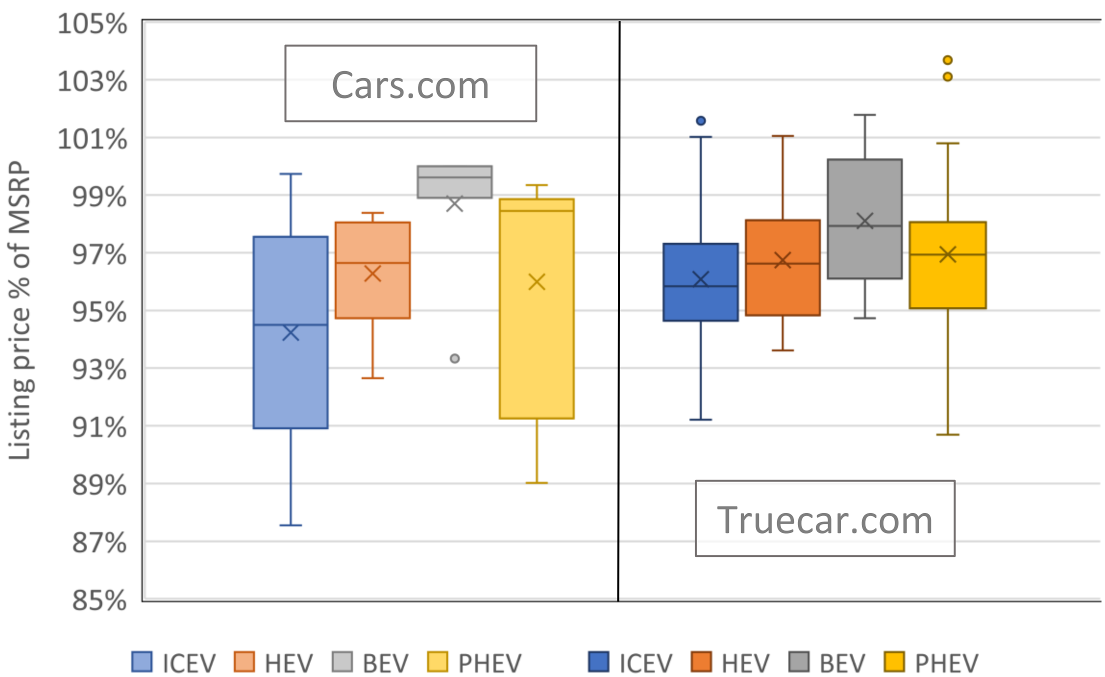

Figure 2: New-vehicle listing price as percentage of MSRP. *x* indicates mean.

To control for the effect of the federal tax incentive for PHEVs and BEVs, we define an adjusted retention rate, ARR_i, such that

$$ARR_i = \frac{P_0 - I - \Delta_i}{P_0 - I}, \qquad i = 1,2,3,\ldots \qquad \text{Eq. 1}$$

where

- ARR_i = the ARR at year i,
- P_0 = the MSRP in the year the vehicle was sold as new,
- Δi = the accumulated depreciation through year i, and
- I = the federal income tax credit applicable to a specific model.

Using the ARR allows us to normalize across MSRPs and powertrain types that qualify for different federal tax credits. As discussed by Zhou et al. (2016), ARR is a more objective metric for comparing depreciation of BEVs, PHEVs, and conventional vehicles; since the Edmunds TMV data are based on real-world value, these data points are in fact more objective relative to this adjusted initial cost. As such, we use ARR. In this case, the ARR is given by

$$ARR_i = \frac{TMV_i}{P_0 - I}, \qquad i = 1,2,3,\ldots \qquad \text{Eq. 2}$$

and the cumulative depreciation through year i is given by

$$P_0 - I - TMV_i = (P_0 - I)(1 - ARR_i), \qquad i = 1,2,3,\ldots \qquad \text{Eq. 3}$$

where TMV_i = the resale value in year i.

Ideally, we would compare actual transaction prices, including state policies and dealer incentives, in addition to the federal tax credit; however, it is very difficult to track these incentives as they change over time and may not be applied to each vehicle. Excluding state and local incentives and manufacturer rebates, nonetheless, artificially underestimates ARR for PEVs, primarily in those states with higher incentives.

A potential impact on residual value when comparing MSRPs and market value estimates in different years is the effect of inflation. However, this effect is small during short time frames and discounting MSRPs and TMVs is beyond the scope of this project. Qualitatively, we consider the potential effect on our results: if we were to discount all historical MSRPs and TMV estimates, all ARRs would be shifted downward, and this effect would be greater for larger-year ARRs. This fact implies that we underestimate the annual depreciation rates obtained when fitting an exponential model to forecast depreciation for the lifetime of any generalized vehicle, as described by Burnham et al. (2021). Since inflation is measured in percentage terms, including the effect of discounting would shift all ARRs down by the same percentage; hence, larger ARRs are overestimated more, in absolute terms.

2.2.2. Depreciation Analysis

We select a 3-year ARR to examine residual-value trends over different MYs for vehicles with various characteristics, such as powertrain, market segment, and size class. We use a relatively short time frame because it allows us to examine a wider range of MYs, as we need *k* years of data to obtain a k-year ARR. Also, there is more variation in ARR in earlier years, which allows us to identify trends across various vehicle characteristics more easily. Finally, we use a 3-year ARR for direct comparison with previous studies (Guo and Zhou 2019; Zhou et al. 2016). When calculating each vehicle's 3-year ARR, we take the mean ARR of a seven-month period from 33 to 39 months after each vehicle's new-market entry. For example, if a vehicle entered the new market in January 2017, our reported 3-year ARR would be the mean of the October 2019 through April 2020 ARR values.

Although we select a short-time-frame (3-year) ARR to examine residual value trends over time, for newer MYs (primarily MY19 and MY20), we do not yet have 3 years of data with which to calculate a 3-year ARR. To estimate the retention rate of these newer models, we fit an exponential function of the following form to the monthly ARR data that we have:

$$ARR_m = b \times exp(k \cdot m) \quad , \qquad \text{Eq. 4}$$

where b is a parameter representing a loss in residual value immediately upon initial sale, k is a parameter of the monthly depreciation rate, and m is the month since market entry. Fitting a model of this form assumes a constant monthly depreciation rate; high R^2 values imply that this simplifying assumption is effective.

For validation, we test this model fitting method on earlier MYs for which we know the actual 3-year ARR. For each MY14 through MY18 vehicle for which we have a 3-year ARR, we fit a model using from 3 up to 20 months of data. Aggregated results by powertrain comparing the model-estimated 3-year ARR with the actual 3-year ARR are shown in Figure 3, as a function of the number of months used for determining the fit. The mean residual is denoted with an x, where the solid bars represent the interquartile range (25^{th} to 75^{th} percentiles) and the error bars represent the models with the greatest discrepancy between the extrapolated ARR and the actual 36-month ARR. When fitting the model on at least seven months of data, the mean residual is less than one percentage point for ICEVs, HEVs, and PHEVs. Since we are interested in aggregated results by powertrain, rather than individual vehicle models, the mean value is of more interest than the spread. For any vehicle for which we have three years of data, we calculate the actual ARR at 36 (±3) months, as described previously. For newer-MY vehicles without three years of data, we estimate the 3-year ARR using the exponential model, given that there are at least seven months of data; vehicles without seven months of data are excluded from our analysis.

As shown in Figure 3, the model fitting tends to overestimate BEV ARRs, even when 7 or more months of data are used, likely owing in part to the smaller number of BEV vehicles we have data for. While this finding does suggest that our BEV 3-year ARR estimates (primarily MY19 and MY20) may be too high, it is important to note that seven months of data is only the cutoff for including a vehicle in our analysis; nearly all MY19 and many MY20 BEVs have significantly more months of data used for the model fit. In general, we expect our MY19 and MY20 BEV 3-year ARR estimates to be within four and five percentage points of the actual value, respectively.

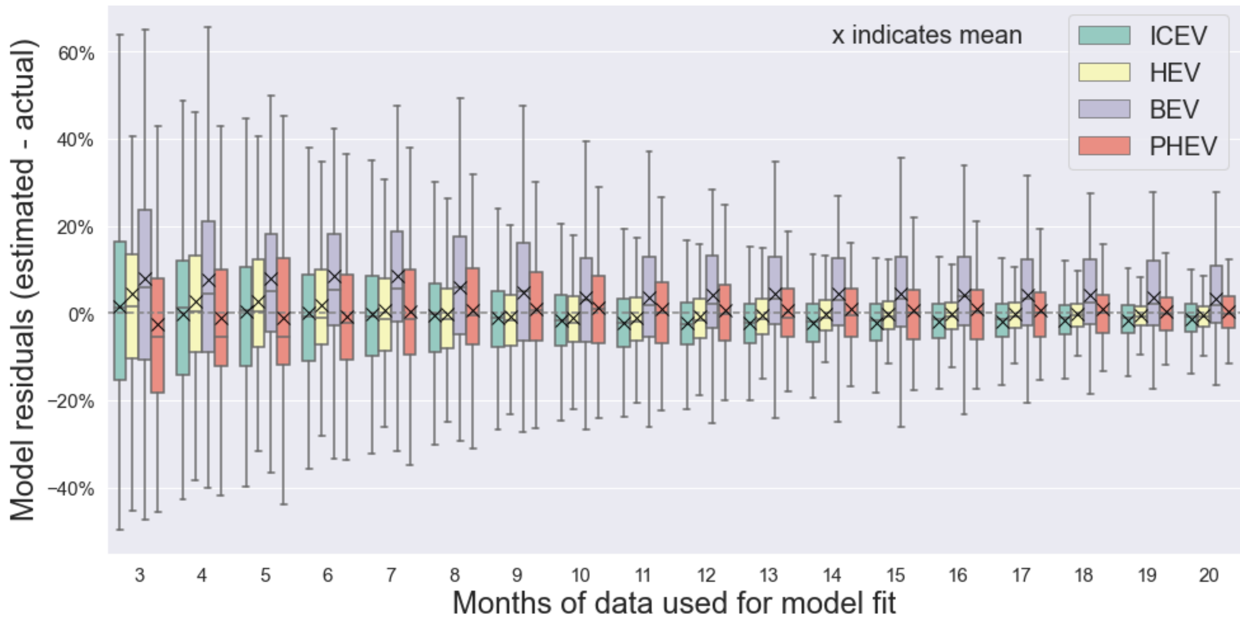

Figure 3: Comparison between model-estimated and actual 3-year ARR for MYs 14-18. Note that positive residuals indicate that the model-estimated ARR is greater than the actual ARR.

Using the new-market entry-date data from fueleconomy.gov (DOE and EPA 2021) and the TMV and MSRP data from Edmunds, we calculate or estimate ARRs for all individual trim lines with at least seven months of TMV data. However, as some vehicle models have more available trim lines than others, we then average ARR values across all trim lines within a vehicle model so that each model has equal weight. The results averaged at the model level are then used in all further figures and results in this report.

We compare results with those of Burnham et al. (2021) to quantify the potential impact of methodological changes on TCO calculations. In short, we fit an exponential function of the form

$$ARR_{i,m,p} = b_{m,p} \times exp\left(k_{m,p} \cdot i\right) \quad \text{Eq. 5}$$

to all of the ARR data in each powertrain (denoted as 'p'), market segment (denoted as 'm') subset; each subset include ARRs for each age, *i*, of each vehicle for which we have data. This process is largely the same for the snapshot and time-series methods, except for a subtle difference: In the case of the snapshot method, the independent variable of the data upon which we fit the exponential function is the years since MY (i.e., year 3 = MY17, since market estimates are from 2020), for multiple MYs and a single calendar year. For the time-series method, the independent variable is also the years since MY, but for a single MY and multiple calendar years (i.e., for MY16, year 3 = calendar year 2019).

As discussed by Kleiner and Friedrich (2017) and Propfe et al. (2012), residual value can be interpreted as a function of both age and VMT, the latter two being highly correlated. For medium- and heavy-duty vehicles, Burnham et al. (2021) use a multi-dimensional model considering both VMT and age of used-vehicle listings, while assuming an average VMT schedule for LDVs and quantifying light-duty residual value as a function of vehicle age. Conversely, Sallee et al. (2016) focus on variations in residual value as a function of VMT instead of as a function of age. Since the Edmunds TMV data used in this report only provide one mileage value per monthly TMV estimate, we are unable to explore the additional effect of VMT on a single vehicle's retention rate. Analyzing variation in mileage means that we must analyze an entirely different vehicle, or the same one of a different age, making it challenging to differentiate the effect of VMT from other variables. Furthermore, vehicle age and VMT are highly correlated in our dataset ($R^2 = 0.92$), possibly indicating that Edmunds simply utilizes a linear relationship between age and mileage when determining its "medium mileage" national average values. As such, it is nearly impossible to distinguish between the effect of age and of VMT in this dataset; by using age as our independent variable, we also capture nearly all the variation in VMT. Since the mileage intervals are not consistent, we examine residual value as a function of vehicle age. In our analysis, we examine average representative driving characteristics; exploring effects of VMT on retention rate is an interesting but separate research question. We do find that there is high correlation between VMT and ARR ($R^2 = 0.78$). Examining the relationship between vehicle age, VMT, and residual value is important future work.

2.2.3. Regression Analysis

To quantify the impact of several important factors, including powertrain, market segment, size class, and automaker, and to make comparisons with previous studies, we perform several weighted least squares (WLS) regression analyses. For our quantitative analysis, rather than averaging the trim-line retention rates to the model level, we retain the trim-line-level results for statistical robustness. To ensure that each vehicle model is still given equal weight, we use a WLS model instead of a more traditional ordinary least-squares model, where the weight for each trim line's retention rate is 1 divided by the number of trim lines within that given vehicle model.

We consider WLS regression models—one on all MYs combined and one each on MY14, MY17, and MY20—to observe trends over time. The dependent variable is 3-year ARR. For comparison with the results of Guo and Zhou (2019), we include the same five independent variables in our regression model: powertrain, market segment, size class, OEM country, and Tesla or not. In future research, we could consider including more variables, such as MSRP and vehicle range. As all of these are categorical variables, we use Boolean dummy variables, indicating whether or not that variable is associated with a given vehicle, to create a linear model of the form

$$\begin{aligned} ARR_{3,v} = \beta_0 &+ \beta_1 \cdot \mathrm{BEV}_v + \beta_2 \cdot \mathrm{ICEV}_v + \beta_3 \cdot \mathrm{HEV}_v + \beta_4 \cdot \mathrm{PHEV}_v \\ &+ \beta_5 \cdot \mathrm{luxury}_v + \beta_6 \cdot \mathrm{mass\ market}_v \\ &+ \beta_7 \cdot \mathrm{car}_v + \beta_8 \cdot \mathrm{light\ truck}_v \\ &+ \beta_9 \cdot \mathrm{Germany}_v + \beta_{10} \cdot \mathrm{Japan}_v + \beta_{11} \cdot \mathrm{Korea}_v \\ &+ \beta_{12} \cdot \mathrm{U.K.}_v + \beta_{13} \cdot \mathrm{U.S.}_v + \beta_{14} \cdot \mathrm{Tesla}_v \end{aligned} \qquad \text{Eq. 6}$$

where $ARR_{3,v}$ is the 3-year ARR of vehicle v. For example, for the Toyota Prius, variables HEV, mass market, car, and Japan will equal 1 and the rest will equal 0. We considered including annual VMT as an additional factor in the regression analysis, to observe its effect on 3-year ARR when other variables are controlled for; however, in all four models, it was not a statistically significant variable. Since there is such high correlation between age and VMT in our dataset and we are holding age constant (at three years) across all vehicles, the VMT is likely not a statistically predictive factor.

3. RESULTS

3.1. RESIDUAL VALUE TRENDS BY VEHICLE CHARACTERISTICS

Figure 4 shows the spread and average 3-year ARRs for each powertrain type in MYs 2012–2020. Note that for many of the MY19 and MY20 vehicles, the 3-year ARR is an estimate using an exponential model, as described in the Methodology section. We observe that the more mature powertrain technologies, such as ICEV and HEV, have more consistent 3-year ARRs over time, while the newer powertrain technologies vary more over time. Similarly, within a single MY, the variation in 3-year ARR of the advanced powertrain vehicles, especially BEVs, is larger than that of ICEVs and HEVs. For most MYs before 2017, PHEVs and BEVs experienced lower retention rates than their conventional counterparts. This is especially true for BEVs, whose ARRs were 10+ percentage points lower in MY15. However, since then, PEVs have increasingly retained value, to the point where they have retained value better than ICEVs and HEVs in recent MYs. The difference in retention rate between ICEVs and HEVs tends to be small, with one experiencing higher 3-year ARRs in some MYs and the other in other MYs.

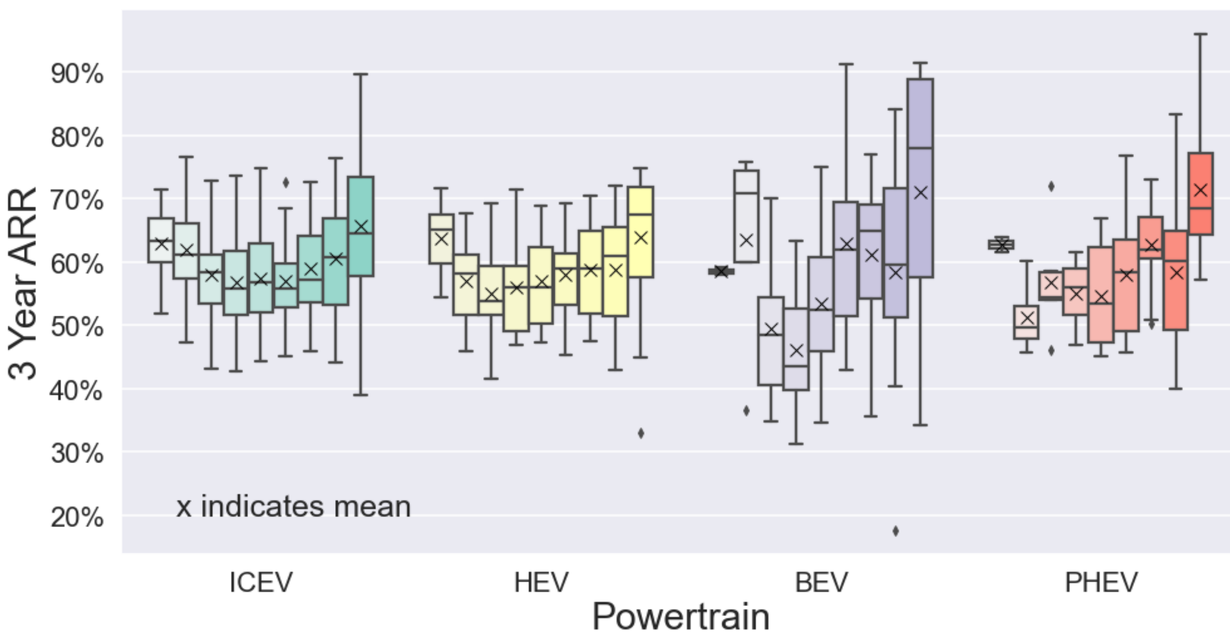

Figure 4: 3-year ARRs by powertrain and MY. Within each powertrain, each box and whisker represent MYs 2012–2020 in order from left to right. *Note:* data for MYs 2012–2020 are on display for all four powertrains, although they are very limited for BEV and PHEV in 2012.

There are several possible explanations for these results. Since 2014 and 2015, increasing capabilities of BEVs have made them much more viable alternatives to their conventional counterparts. This factor carries over to the used-vehicle market, hence the higher 3-year ARRs in recent MYs. As shown in Figure 5, the sales-weighted BEV range, a measure of how far a BEV can drive on a single charge, which is a common indicator of BEV capability, increased from around 130 miles in 2014 to over 300 miles in 2020 (ANL 2021). Relatedly, it is reasonable to assume that decreasing prices of new BEVs drive down the prices of used PEVs (Holweg and Kattuman 2006). Figure 5 indicates that the sales-weighted MSRP of BEVs (using MSRP of the lowest-cost trim line by model) increased only slightly from 2014–2015 to 2017–2018, when the 3-year ARR of the MY14–15 BEVs is, on average, measured, despite the electric range nearly doubling in the same time frame. This means that in 2017–2018, potential BEV consumers could purchase a new BEV for about the same price as what the used BEVs then on the market were sold for when new, but with significantly better specifications and capability. Note that the MSRP values are not inflation-adjusted, which would make the MSRPs of these two years even more similar. A contributing factor to this development is the release of the Tesla Model 3, which was first sold in July 2017 and was the top-selling PEV in 2018. The MY17 Model 3 has a 310-mile range and a starting MSRP of $44,000, putting it at the MY14–15 market average MSRP, but over double the MY14–15 market average electric range. It is likely that the release of the Tesla Model 3 in 2017 was a significant factor in driving down the market value, and thus ARR, of used MY14–15 BEVs.

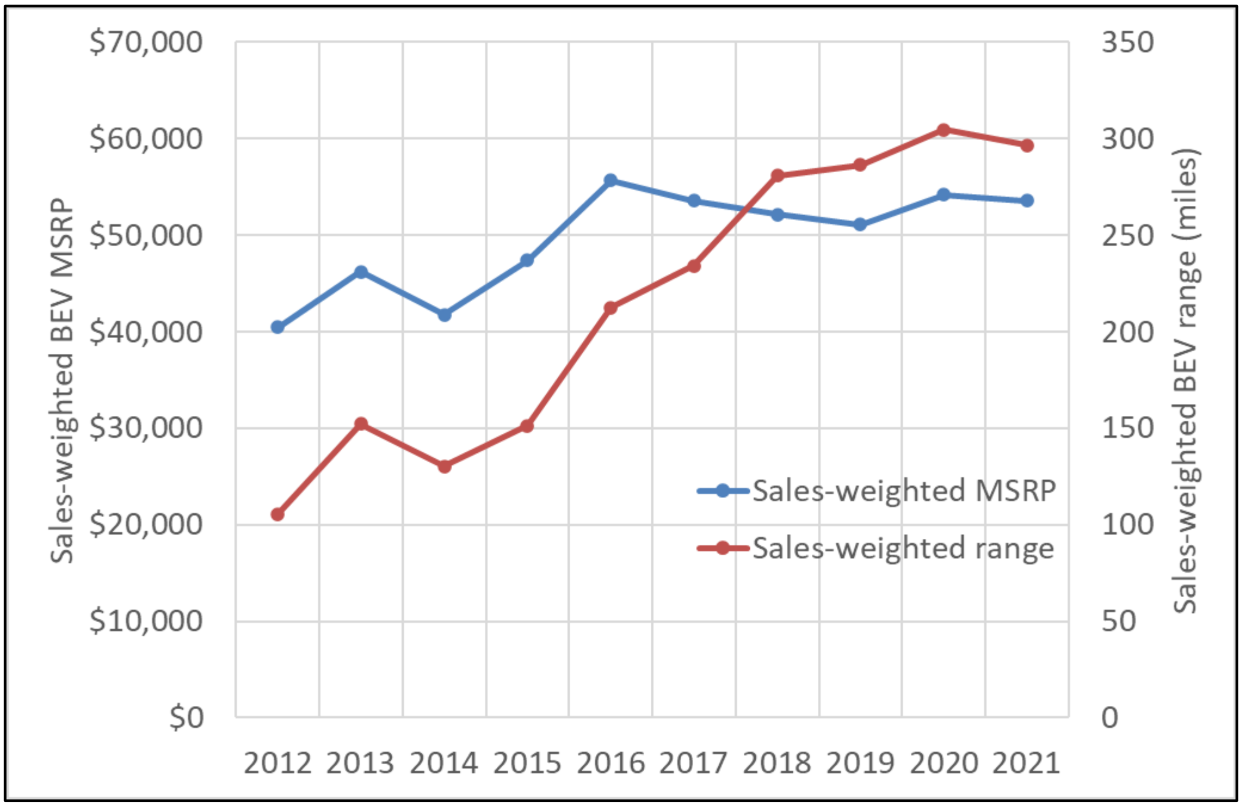

Figure 5: Sales-weighted MSRP and electric range of all BEVs, 2012–2021. (2021 data through May.)

To examine trends in retention rate over different MYs for additional vehicle characteristics, we further disaggregate these results by market segment and by vehicle size class. Figure 6 and Figure 7 disaggregate the results by powertrain and market segment, and powertrain and size class, respectively, and show the mean 3-year ARR of all vehicle models within a given MY, powertrain, and market segment/size class. For analysis by size class, we group all size classes into one of the two regulatory size classes, i.e., light truck (Small SUV, Standard SUV, Minivan) and car (everything else). Figure indicates that there is very little difference in ARR between luxury and mass-market vehicles for ICEVs and HEVs; however, the difference is greater for PEVs. Luxury BEVs consistently retain a higher value than mass-market

BEVs, largely driven by high retention rates for Tesla models, though this differential has narrowed slightly in recent years. As shown in Figure , light trucks consistently retain their value better than cars; this is true for all four powertrain types and all MYs. However, the difference between the two regulatory size classes varies across the powertrain types; it is largest for HEVs and BEVs and smaller for ICEVs and PHEVs.

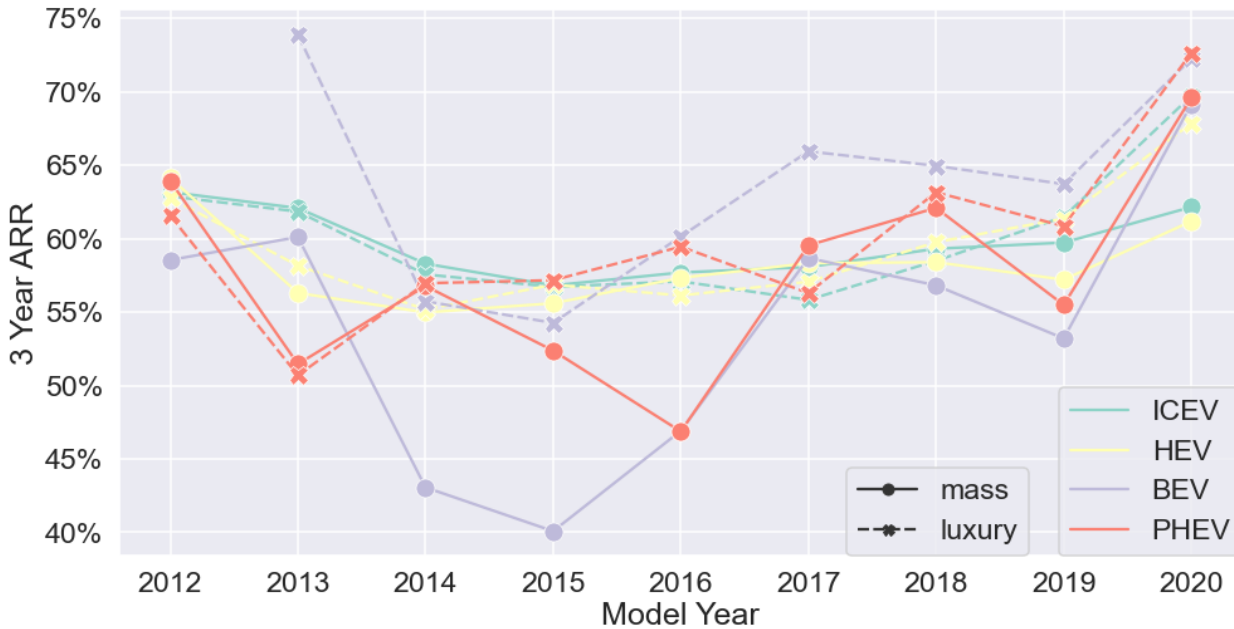

Figure 6: Mean 3-year ARR by MY, powertrain, and market segment. The colors denote the powertrains, the solid lines and circles denote mass-market vehicles, and the dotted lines and x's denote luxury vehicles.

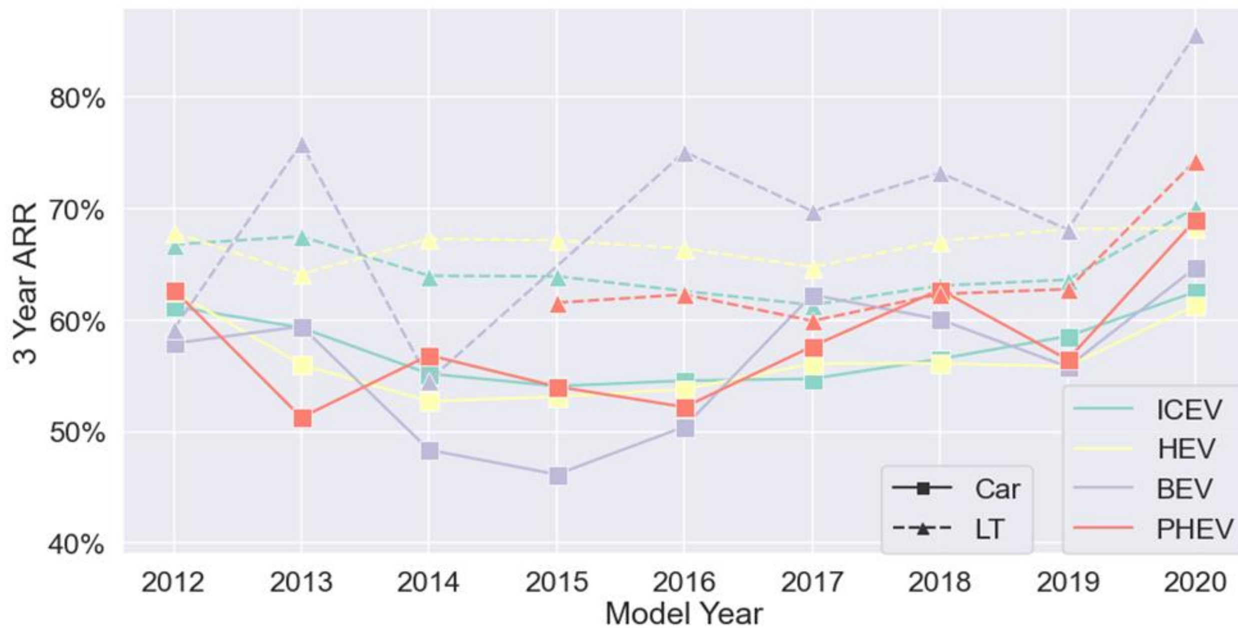

Figure 7: Mean 3-year ARR by MY, powertrain, and regulatory size class. The colors denote the powertrains, the solid lines and squares denote cars, and the dotted lines and triangles denote light trucks.

Table 3 shows WLS regression results obtained using the predictive model described in Eq. 6 in Section 2.3.3. When looking at a single MY as opposed to all MYs combined, the regression model tends to be more predictive (higher R^2), which is unsurprising since trends by various characteristics have changed over time. Interestingly, when one moves from MY14 to MY17 to MY20, the R^2 of the model decreases. This finding may be due to the diminishing differences in 3-year ARR between powertrains, reducing the predictive power of this variable. In general, most of these variables are statistically significant in each of the regression models. Again, we see little difference between luxury and mass-market vehicles, but substantial differences between cars and light trucks for all the models. OEM country also tends to be a significant variable, with Japan and South Korea increasing the 3-year ARR more than the other countries. Quantitatively, we see that Tesla models hold their value quite well: on average, a Tesla vehicle has a higher 3-year ARR by about 25 percentage points than a modeled American luxury BEV. This finding is consistent with other recent studies (Guo and Zhou 2019) and industry reports (Blackley 2021).

Table 3: Comparison of WLS Regression Models for Three-Year Adjusted Retention Rate

Coefficients of factors in WLS regression models, dependent variable: 3-year ARR				
Variable	**MY2014**	**MY2017**	**MY2020**	**All MYs**
BEV	-0.031***	0.087***	0.014	0.023***
ICEV	0.086***	0.044***	0.077***	0.069***
HEV	0.062***	0.037***	0.059***	0.058***
PHEV	0.109***	0.076***	0.122***	0.094***
Luxury	0.110***	0.121***	0.163***	0.128***
Mass Market	0.115***	0.123***	0.110***	0.116***
Car	0.063***	0.089***	0.104***	0.085***
Light Truck	0.162***	0.155***	0.169***	0.160***
Germany	0.072***	0.013	0.009	0.044***
Japan	0.088***	0.085***	0.049***	0.085***
South Korea	0.042***	0.099***	0.089***	0.077***
UK	-0.007	0.032**	0.107***	0.034***
US	0.030***	0.015	0.018	0.005
Tesla	0.304***	0.161***	0.291***	0.248***
Constant	0.225***	0.244***	0.273***	0.245***
R^2	0.609	0.366	0.331	0.325
Adjusted R^2	0.596	0.350	0.314	0.323
Note: *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$				

3.2. IMPACTS OF COVID-19 ON VEHICLE RESIDUAL VALUE

The COVID-19 pandemic and its far-reaching consequences had significant impacts on the vehicle market in 2020 and 2021, some of which are still apparent. Reductions in new-vehicle sales and the threat of recession changed buying habits. Vehicle resale prices dropped significantly during the first few months of the pandemic.

Figure 8 shows the month-over-month average change in used-vehicle valuation, with the months on the horizontal axis showing the appreciation in that month from the previous one (e.g., negative values in January 2019 indicate depreciation from December 2018 to January 2019). Normal vehicle depreciation behavior, exhibited throughout 2018, 2019, and early 2020, shows a depreciation of approximately 1% to 3% per month. As can be seen from Figure 8, since April 2020, there has been a marked change from this typical depreciation trend. All of the newer-MY vehicles experienced extremely high depreciation from March to April of 2020, followed by positive numbers from April to May of 2020, indicating that used vehicles appreciated in value. This monthly appreciation occurred in several additional months since then. COVID-19 has led to an increase in used-car sales attributable to a scarcity of new cars from auto plants, resulting from earlier shutdowns, and a greater increase in auto usage in these two years as people avoided mass transportation, all combined with more caution about spending on big items. Such a trend has remained as the impacts of inflation and indications of higher interest rates have begun to be felt. These factors have combined to drive up the prices of used vehicles since the start of the pandemic (Rosenbaum 2020).

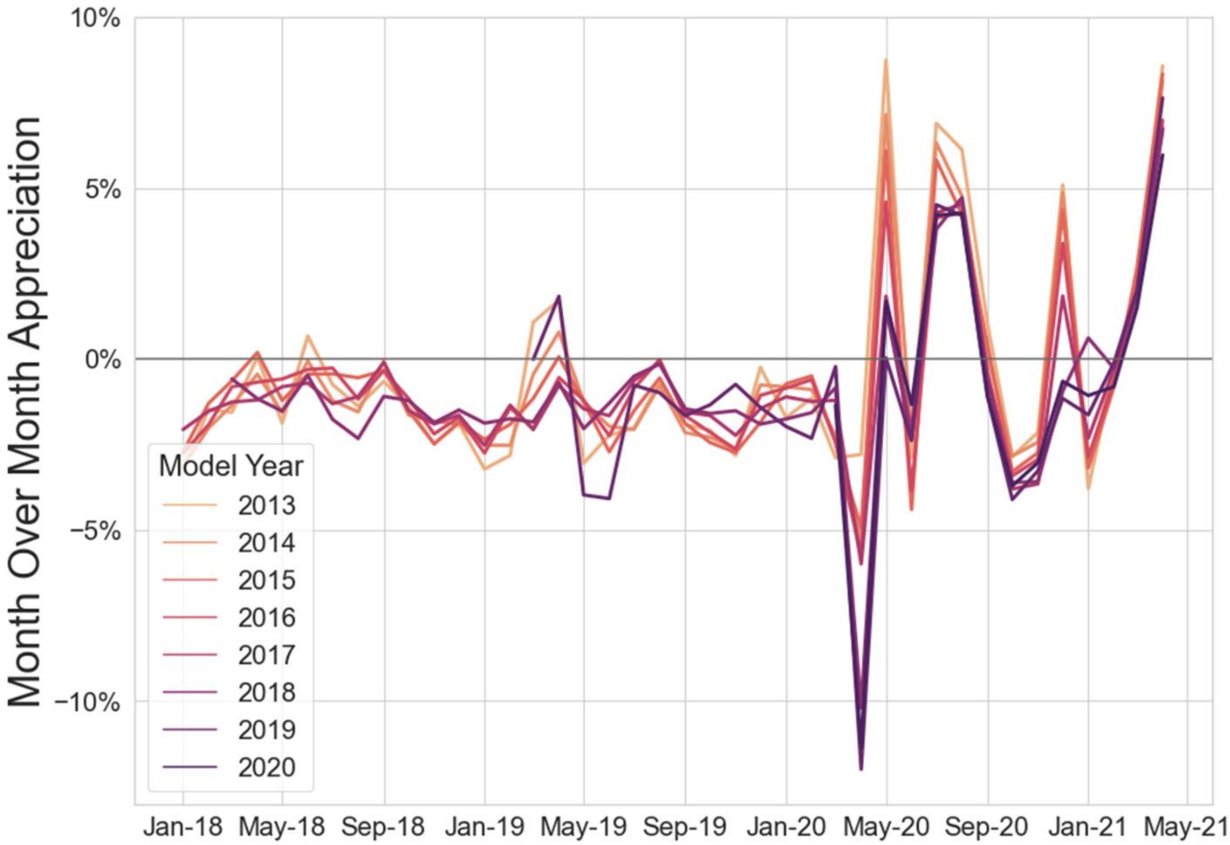

Figure 8: Month-by-month change in used-vehicle prices

To examine the effect of COVID-19 on the results presented in Figure , we performed the same analysis after removing all TMV estimates from the COVID-19 months with the most abnormal vehicle resale prices (April through August 2020). A comparison between the 'with COVID-19 months' and 'without COVID months' is shown in Figure 9. The results using all months' data, as in Figure (now grouped by MY), are replicated and shown in the brighter color tones while the results without the five COVID-19 months are shown behind the first set, faded. In general, there is little difference between including and excluding the five COVID-19 months. While there is some difference in the spread of the 3-year ARRs, especially in recent MYs, there is very little difference between the means. As such, we do not make any adjustment for the COVID-19 pandemic and use all months' data for all further analysis in this report.

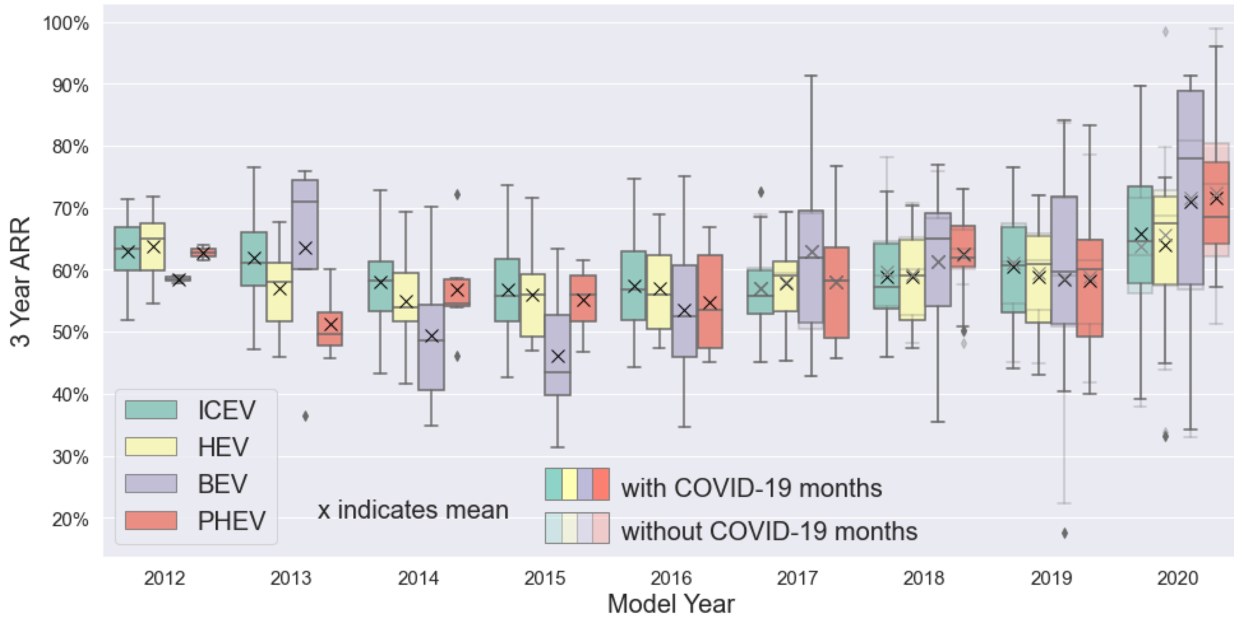

Figure 9: Comparison between analysis results including (brighter colors) and excluding (behind those, faded) COVID-19 months (Apr.–Aug. 2020). (A horizontal line indicates the median and x indicates the mean. A horizontal line across the bar that is not close to the x likely indicates (1) a small dataset size, and (2) the presence of outlier(s). In the case of the purple bar for 2013, it is likely due to both reasons, but we can specifically see the outlier dot around 38%.)

3.3. COMPARISON BETWEEN SNAPSHOT METHOD AND TIME-SERIES METHOD

As previously described, one objective of this report is to identify how using time-series data could affect calculations of TCO. This study compares results from the time-series methodology with recently published data from Burnham et al. (2021), which were obtained using the snapshot method. The left graph in Figure 10 shows the snapshot method; each point is the mean ARR in 2020 for different MY vehicles, aggregated by powertrain and market segment subsets. As described by Burnham et al. (2021), to estimate the ARR for the entire lifetime of a vehicle, an exponential function is fit to the same data that is used to calculate the mean ARRs for each MY for each subset (Figure 10, left). The right graph in Figure 10 shows a time-series analog; each point is the mean ARR in different years for MY16 vehicles, aggregated again by powertrain and market-segment subsets. For comparison with the snapshot method, we similarly fit an exponential function to the same data that are used to calculate the mean ARRs for each year for each subset. We select MY16, as it provides a balance between having sufficient data to fit a model and being relatively recent, about in the middle of the range of MYs used in the snapshot analysis. The blue boxes in Figure help identify the relationship between the two graphs. The points within the boxes represent TMV estimates for MY16 in 2020 in both graphs; they are similar, with minor variations attributable to differences in the datasets. Qualitatively, there are many similarities between the two, such as the observation that BEVs and PHEVs hold their value well in early years before dropping off.

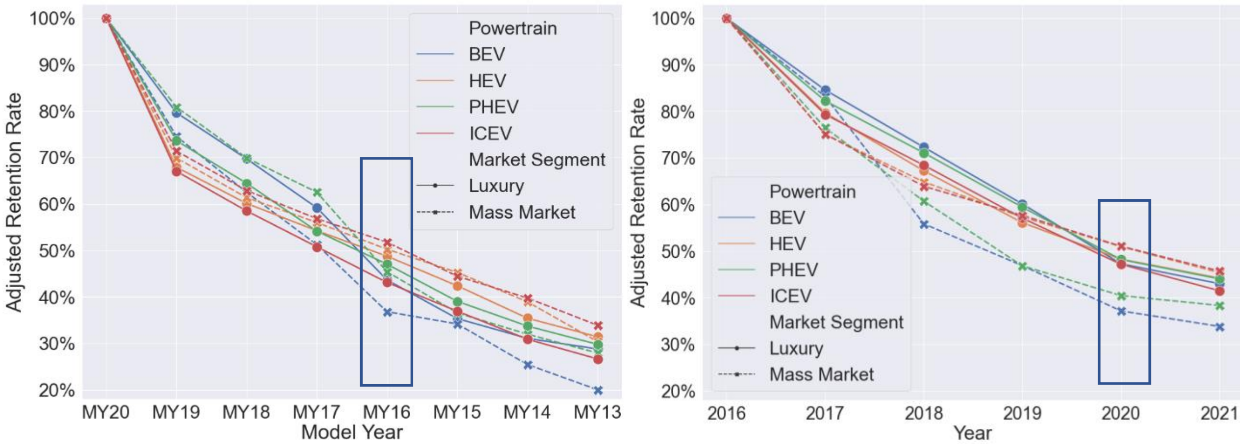

Figure 10: ARR over time: Comparison between snapshot and time-series methods.

We are also able to quantify the potential impact on the TCO calculations. As described by Burnham et al. (2021), to forecast depreciation for the lifetime of any generalized vehicle, we fit an exponential model to the ARR data points as written earlier in Eq. 5 (shown again below). Here the adjusted retention rate $ARR_{i,m,p}$ as a function of age (i), powertrain type (p), and market segment classification (m) is expressed as

$$ARR_{i,m,p} = b_{m,p} \times exp(k_{m,p} \cdot i), \qquad \text{Eq. 5}$$

where $\exp(k_{m,p})$ is the percentage value retention from the previous year for a vehicle of market segment classification m and powertrain p, and $b_{m,p}$ is a scaling factor representing the loss in residual value immediately upon initial sale. As $b_{m,p}$ and $k_{m,p}$ are parameters determined by the regression analysis, we can compare the parameter results generated by the two methods. The comparison, shown in Table 4, indicates that the results of the two methods are quite similar. The largest difference between the two in both depreciation rate and first-year value adjustment is for luxury HEVs, with moderate differences for luxury ICEVs and PHEVs as well.

Table 4: Annual Depreciation Rates and First-year Adjustment by Powertrain and Market Segment. For each cell, the value on the left represents the snapshot method and the value on the right represents the time-series method (i.e., snapshot | time-series).

Annual Depreciation Rates, 1-exp($k_{m,p}$)				
	BEV	**HEV**	**ICEV**	**PHEV**
Mass-market	19.2%	19.9%	12.1%	11.9%	11.3%	11.6%	16.6%	16.2%
Luxury	17.4%	16.5%	12.0%	14.0%	14.5%	15.4%	14.3%	15.1%
Additional First-Year Value Adjustment, $b_{m,p}$				
	BEV	**HEV**	**ICEV**	**PHEV**
Mass-market	92.2%	93.3%	80.0%	83.8%	80.3%	83.1%	98.6%	86.0%
Luxury	97.9%	100.8%	77.8%	90.6%	79.5%	94.0%	85.9%	96.6%

Using the exponential model in Eq. 5, we can then estimate the ARR of any vehicle at any age. We use Eq. 5 and the parameters in Table 4 to calculate the ARR using these two methods after 15 years, which is the typical lifetime used in the base-case TCO analyses. The results, shown in Table 5, indicate that the snapshot method provides higher 15-year ARRs in more cases than those demonstrating the reverse pattern. The difference in 15-year ARR between these two methods is between -1.2 and +2 percentage points, depending on the powertrain and market segment. This is a small difference when considering a typical MSRP of $20,000–$50,000.

Table 5: Base-case TCO Calculation Input Comparison for 15-Year ARRs. For each cell, the value on the left represents the snapshot method and the value on the right represents the time-series method (i.e., snapshot | time-series).

<table>
<tr><th colspan="5">15-year ARRs for snapshot and time-series methods (i.e., snapshot | time-series)</th></tr>
<tr><th></th><th>BEV</th><th>HEV</th><th>ICEV</th><th>PHEV</th></tr>
<tr><td>Mass-market</td><td>3.77% | 3.34%</td><td>11.56% | 12.53%</td><td>13.29% | 13.07%</td><td>6.48% | 6.07%</td></tr>
<tr><td>Luxury</td><td>5.57% | 6.74%</td><td>11.43% | 9.43%</td><td>7.58% | 7.65%</td><td>8.49% | 8.29%</td></tr>
</table>

Light trucks have been seen to retain their value better than cars. Following Burnham et al. (2021), we account for differences in retention rates across size classes by performing a size-class adjustment after determining the parameters $b_{m,p}$ and $k_{m,p}$ as described above. We calculate the average difference between the ARRs of the two size classes (cars and light trucks) within each powertrain type (but not segmenting by luxury/mass-market because of small sample sizes), and adjust the ARRs for each powertrain type and market segment as a proportion of the average ARR for each year by

$$ARR_{i,p,k} = ARR_{i,p} \times \left(1 \pm S_p / 2\right), \quad \text{Eq. 7}$$

where i is the age of the vehicle, p labels each powertrain, k represents the size class, and S_p is the adjustment for the size of each powertrain. A comparison between these proportional differences for cars and light trucks for the two methods is shown in Table 6. For all powertrain types for both methods, we make an upward adjustment for light trucks and a downward adjustment for cars. The largest difference between the two methods occurs for BEVs and ICEVs, with small differences for the other two powertrain types.

Table 6: Proportional Differences (of Average ARR) between Size Classes (Cars and Light Trucks). For each cell, the value on the left represents the snapshot method and the value on the right represents the time-series method (i.e., snapshot | time-series).

Powertrain	BEV	HEV	ICEV	PHEV
Difference between size classes	21.6% | 32.8%	22.6% | 18.3%	3.2% | 10.7%	7.6% | 10.8%

As illustrated above, the difference in 15-year retention rate (the base-case TCO lifetime) between these two methods is less than 2 percentage points, depending on the powertrain and market segment. The difference in size-class adjustment between these two methods is at most about 11%. Since this is the proportional difference of *average* ARR and the 15-year ARRs shown in Table 5 are on the order of 3%–13%, the difference in size-class adjustment affects the 15-year ARR by only about 1 percentage point at most. Therefore, the greatest potential net effect on TCO of using the time-series method rather than the snapshot method is about 3% of the original value of the vehicle.

4. DISCUSSION AND CONCLUSIONS

This study explores the residual value trends over various MYs of different powertrain technologies and several other vehicle characteristics using historical TMV data from Edmunds. The primary objectives of this study were to examine how different powertrains' residual values have evolved over time amid rapidly improving PEV technology, accounting for important factors such as market segment, size class, and OEM country, and to compare depreciation trends between competing calculation methods in order to identify the potential impact on TCO calculations. We find that:

1. After exhibiting quite low 3-year ARRs in MYs 2014–2016, PHEVs and especially BEVs have increasingly retained value, to the point where they have retained value better than their conventional counterparts in recent years;
2. There is very little difference in retention rate between luxury and mass-market models for ICEVs and HEVs; however, luxury BEVs consistently outperform mass-market BEVs, largely driven by high retention rates for Tesla models;
3. Light trucks consistently retain their value better than cars for all four powertrain types and all MYs; and
4. The difference between the snapshot and time-series methods, and therefore the potential impact on TCO calculations, is small, resulting in at most a net effect on TCO of 3% of the vehicle's original value.

A primary objective of this study was to examine how different powertrains' residual values have evolved over time, as few, if any, researchers have looked at these trends over time. Understanding the residual value/depreciation of vehicles with newer, more advanced powertrain technologies is crucial in identifying when these vehicles become cost-competitive with their conventional counterparts. Changes in vehicle characteristics may lead to changes in residual value, affecting estimations of when cost parity of advanced vehicle technologies may occur.

We find that more mature powertrain technologies, such as ICEV and HEV, have more consistent 3-year ARRs over time, while those of the newer powertrain technologies vary more over time. After experiencing quite low 3-year ARRs in MYs 2014–2016, PHEVs and especially BEVs increasingly retain value, to the point where they have retained value better than their conventional counterparts in recent years. It is important to note that this finding is just for the 3-year residual value and may not extend to the entire lifetime of a vehicle; however, it is clear that these advanced powertrain types have increasingly held their value over the most recent 5–7 MYs. A potential explanation is that PEVs have seen rapid increases in technology and capability without a significant rise in price, driving down the demand for and therefore the price of older, used PEVs. The fact that we have seen comparable or higher PEV retention rates in the last four years may also suggest that consumers increasingly do not perceive new PEVs to have substantially higher capabilities than several-year-old used vehicles. As was shown in Figure 4, the U.S. sales-weighted BEV electric range increased only 5.6% from 2018 to 2021, from 280 to 296 miles, though this is true globally as well (IEA 2021).

Interestingly, perceived depreciation of both PEVs and ICEVs also affects new PEV adoption. If a lessor expects a lower residual value for a given vehicle at the end of the lease term, the monthly payments on a lease will be higher to account for the greater deprecation rate. Vehicle purchasers do tend to be less focused on a comprehensive TCO calculation considering depreciation. A survey of respondents in Europe estimated that depreciation was the single largest cost of owning and operating a vehicle, yet only half of respondents had an approximate knowledge of depreciation rates, and only 8% planned to use depreciation rates in an ex-ante cost computation before purchase (Hagman et al 2017). However, concern about potential obsolescence of ICEVs may lead consumers to delay purchase of a conventional vehicle or to switch to an electric vehicle (Neil 2018; Huetter 2021). Despite the COVID-19 pandemic's negative effect on vehicle sales, U.S. PEV sales only decreased by 3.8% from 2019 to 2020 compared with a 15.1% decrease in total LDV sales. U.S. PEV sales increased by over 100% in 2021 relative to 2020, compared to only a 3.3% increase in LDV sales (ANL 2021).

Disaggregating powertrain by market segment, we find that there is very little difference in retention rate between luxury and mass-market ICEVs and HEVs; however, the difference is greater for PEVs. Luxury BEVs consistently retain higher residual value than mass-market BEVs, and Tesla vehicles in particular hold high residual values. Disaggregating powertrain by size class reveals that light trucks consistently retain their value better than cars; this is true for all four powertrain types and all MYs. However, the difference between the two regulatory size classes varies across the powertrain types; it is largest for HEVs and BEVs and smaller for ICEVs and PHEVs. The difference between the two size classes is quite consistent over time for the more mature powertrain technologies, ICEV and HEV, and is more volatile for PEVs.

Our regression model for 3-year ARR, including the variables powertrain type, market segment, size class, OEM country, and Tesla or not, is less predictive for recent MYs than for older ones. This finding may be due to diminishing differences in 3-year ARR between powertrains, decreasing the predictive power of this variable. We find that regardless of MY, many of the variables included are statistically significant. Finally, we find that Tesla vehicles hold their value quite well, experiencing 3-year ARRs up to 25 percentage points higher than similar non-Tesla vehicles.

The COVID-19 pandemic has changed typical depreciation behavior. Since April 2020, used vehicles have experienced extreme and unusual depreciation trends, actually appreciating in value at times because of high purchase demand. However, there is little difference between including or excluding the five COVID-19 months in estimating the 3-year ARRs for all MYs.

A second primary objective of this study was to compare depreciation trends between the snapshot and time-series methods to identify the potential impact on vehicle cost calculations. The results used by Burnham et al. (2021) were based on the snapshot method, which does not actually track the residual value of a single vehicle over time, but rather obtains a "snapshot" of the residual value of multiple MYs at one point in time. The time-series method, which tracks the residual value of a cohort of vehicles from the same MY over time, is a more accurate way of examining depreciation trends over different MYs, which is especially important amid recent rapidly advancing PEV technology.

Qualitatively, we find that the difference between the snapshot and time-series methods, and thus the potential impact on TCO calculations, is small. Quantitatively, we find that the difference in 15-year ARR, a typical TCO lifetime, between these two methods is between -1.2 and +2 percentage points, depending on the powertrain and market segment. The difference in size-class adjustment between these two methods also affects 15-year ARR by only about 1 percentage point at most. Therefore, we expect the greatest potential net effect on TCO of using the time-series method rather than the snapshot method to be about 3% of the original value of the vehicle. In considering the potential range of values for some of the other key variables included in TCO calculations, this is a relatively insignificant effect.

One of our most important findings is that PEVs now maintain value more effectively than before, demonstrating that they are increasingly comparable to their ICEV and HEV counterparts. This is an important indication that consumer confidence in PEVs is growing amid rapid advancements in advanced powertrain capability. Improving charging infrastructure availability may also play a role here, but our data cannot directly capture that impact. Since low residual values have long been a market barrier to widespread purchase of new PEVs, this finding is a promising sign for future PEV adoption.

An important stipulation is that our analysis of BEV and PHEV retention rates incorporates current federal incentives. Further technology research and development may accelerate the overall adoption of PEVs by reducing new-purchase costs and simultaneously increasing residual value. However, without specific incentives for used vehicles, higher used-vehicle prices may reduce penetration of these low-emission vehicles in disadvantaged communities. Incentivizing PEV adoption could be an effective way to increase electric travel, which would eventually result in decreased fossil-fuel consumption and emissions.

As discussed above, we did find that the difference in depreciation between the snapshot and the time-series method has little effect on TCO calculations. While this observation is promising, these results are based on MY16 vehicles. In the time since these vehicles first came onto the market, advanced powertrain technologies have continued to undergo rapid advancements. Therefore, continuing to track residual values of newer-MY PEVs will be important work, both to confirm that these vehicles are indeed holding their value as well as conventional counterparts through three years and to observe the potential effect on TCO. Furthermore, additional data sources should be used to validate our findings, which may be subject to biases associated with a single data provider. As more PEVs continue to become available in used-vehicle markets, future research in this area will be important to further support our finding that PEVs retain value as well as or better than their ICEV and HEV counterparts.

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